Hiring through Startup Acquisitions:
Preference Mismatch and Employee Departures

by

J. Daniel Kim
MIT and US Census Bureau

Abstract

This paper investigates the effectiveness of startup acquisitions as a hiring strategy. Unlike conventional hires who choose to join a new firm on their own volition, most acquired employees do not have a voice in the decision to be acquired, much less by whom to be acquired. The lack of worker agency may result in a preference mismatch between the acquired employees and the acquiring firm, leading to elevated rates of turnover. Using comprehensive employee-employer matched data from the US Census, I document that acquired workers are significantly more likely to leave compared to regular hires. By constructing a novel peer-based proxy for worker preferences, I show that acquired employees who prefer to work for startups – rather than established firms – are the most likely to leave after the acquisition, lending support to the preference mismatch theory. Moreover, these departures suggest a deeper strategic cost of competitive spawning: upon leaving, acquired workers are more likely to found their own companies, many of which appear to be competitive threats that impair the acquirer's long-run performance.

Keyword*:*

JEL Classification:

1 Introduction

A vast literature on organizations has long explored how firms gain advantage by hiring, developing, and retaining human capital (Becker 1962; Coff 1997; Acemoglu and Pischke 1998; Lazear and Shaw 2007; Teece 2011). In addition to conventional hiring, whereby an individual job seeker and an employer agree to an employment contract, firms may bring in talent through other channels. Especially in tight labor markets, firms can hire by acquiring other companies that house high-quality workers (Ouimet and Zarutskie 2016). This practice is especially common among startup companies whose most valuable – if not the only – asset is their human capital (Chatterji and Patro 2014). Consistent with this view, Mark Zuckerberg once remarked, "We buy companies to get excellent people."

While startup acquisitions allow the buyer to strategically select and hire a team of workers who have proven to work together productively, this hiring method may be contentious from the perspective of the employee. Unlike regular hires who *choose* to join a new employer, most acquired workers do not have a voice in the decision to be acquired – much less by which firm to be acquired.[1] In theory, this lack of worker agency in acquisitions may lead to poor matches between the acquired workers and the acquiring firm. The resulting preference mismatch is likely more pronounced when an established company acquires a startup because they are fundamentally different types of organizations with contrasting cultures (Saxenian 1996; Turco 2016) and structures (Hannan and Freeman 1984; Baron, Hannan, and Burton 1999; Sorensen 2007). As a result, startup acquisitions may result in high rates of employee exits.

Consider the case of Dialpad Communications,[2] which was acquired by Yahoo in 2005. In addition to Dialpad's nascent internet-based calling technology, Yahoo's key motivation in the acquisition was the talent responsible for the early-stage product. Upon the acquisition, almost all of the 40 employees from Dialpad initially joined the acquirer to help develop its own internet-calling software. However, despite the economic incentives to stay,[3] disagreements inside the organization led more than 70% of the former Dialpad employees to leave the firm within three years. Among the departing individuals, the shared motivation was their incompatibility with a large company's bureaucratic environment that prioritized procedures and coordination at the expense of speed and execution. Yahoo's voice-over-IP business struggled to scale, leading the company to eventually shut down the business.

In this paper, I empirically investigate the effectiveness of startup acquisitions as a hiring strategy. To that end, I assemble a comprehensive set of high-tech startup acquisitions in the

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[1] For example, Eric Jackson, a former executive at PayPal, describes in his book "The PayPal Wars" that he along with most of the PayPal employees were not aware of the acquisition decision until the final deal was reached and publicly announced. Only the top management team from both companies as well as early investors were involved in the deal-making.

[2] Interviewed by the author on May 31, 2018.

[3] Typically, employment contracts used in startup acquisitions offer employee stock options with stay-incentives, such as a vesting schedule of three to four years. See (Coyle and Polsky 2013) for more on standard equity incentives used in startup acquisition.

US between 1990 and 2011 by using employee-employer matched data from the US Census. The resulting sample contains roughly 4,000 high-tech startup acquisitions, coupled with 350,000 workers from the target firms and approximately 7 million workers who are hired at the acquiring firms in the same year as the acquisition. Then, I compare the career paths of the acquired workers versus observationally similar regular hires at the same buyer firm with attention paid to not only the retention outcomes, but also the destinations of the departing employees (e.g., joining another firm vs. founding a new firm).

I provide the first large-scale evidence that acquired startup workers exhibit much higher turnover relative to observationally similar organic hires at the same buyer firm. Acquired workers are almost twice as likely to leave as their counterparts who are conventionally hired. Consistent with the Jovanovic (1979) model of worker tenure and turnover, the differences in departure are highest in the first year and monotonically decline thereafter, as acquired workers who are "good fits" tend to stay with their new employer.

Next, I advance the preference mismatch theory as the mechanism that drives the high turnover among acquired workers. I develop and test the hypothesis that the turnover effect is most pronounced among acquired workers who have a strong ex-ante preference for working for a startup rather than an established company. To measure the employees' preferences for working for a young versus established company, I construct a novel proxy based on the turnover patterns of the target startup's former employees. More specifically, I track the departures of startup employees *prior* to the acquisition along with their destinations. While these former employees do not directly influence the behavior of the acquired employees because they are not present at the time of the acquisition, their decisions to join a young firm or an established company provide useful information for peer-based prediction of employee mobility decisions.

Two central insights build the foundation for using peer turnover patterns to proxy for co-workers' preferences for employers. First, job transitions are not random: they are intentional choices that workers make, revealing their preferences for employers. Simply put, a worker's decision to join a particular firm – and thereby *not* join another employer – demonstrates her relative value of the two firms based on both pecuniary and non-pecuniary factors (Sorkin 2018). When aggregated up, these mobility choices characterize the average tendency for a firm's workers to flow to startups rather than established firms. Second, job transitions by former colleagues are especially relevant because they resemble the behavior of the acquired startup employees. Since both the acquired and former employees initially selected into joining a particular startup rather than other potential employers, these workers likely exhibit similar preferences for employment. Following this logic, I define workers to have a strong preference for startup employers if their former colleagues – who leave prior to the acquisition – systematically tend to move to other young companies.

I find that the pre-acquisition departure patterns strongly predict the acquired employees' decision to stay with the buyer. In short, startup employees who highly prefer to work for startups are the most likely to leave following an acquisition. Therefore, ex-ante preferences for employer types largely explain why some workers tend to stay with the acquirer while others leave. Furthermore, this finding provides a managerial tool to diagnose the talent retention potential of an acquisition target by learning from the prior employee turnover patterns.

Lastly, I show that the departures among acquired workers are strategically costly. Upon leaving, acquired workers are significantly more likely to start their own firms – disproportionately in the same industry as the original target firm. Consistent with retention, this effect is strongest among those who strongly prefer to work for startups. While these acquisition-induced entrants could be new competitors or complementors operating in the same industry space, they appear to exert competitive pressures on the acquirer. The buyer firm's long-run performance is negatively related to the intensity of post-acquisition spawning by the target employees, and this negative relationship grows with industry similarity.

More broadly, this study, in two ways, sheds light on the central role of worker choices during an organizational change. First, when workers are imposed with a new employer – as in the case of acquisitions for most employees – such abrupt organizational shift results in excessive turnover among these employees relative to organic hires who choose to join the same firm. This is consistent with – and perhaps helps explain – the cultural clash (c.f., Cartwright and Cooper 1992; Van den Steen 2010) and integration issues (Puranam, Singh, and Zollo 2006; Paruchuri, Nerkar, and Hambrick 2006; Hoberg and Phillips 2017) that frequently pervade mergers and acquisitions. Second, workers' decisions to join young versus established companies are intentional choices that they make, thereby revealing one's preferences for employer types. When these mobility patterns are aggregated up, they provide a powerful proxy for preferences that allow for the prediction of peer workers' retention behavior following an acquisition.

The rest of the paper is as follows. Section 2 develops the theoretical background and presents a set of testable hypotheses. Section 3 describes the empirical setting and the underlying data. Section 4 presents the main results on the turnover and spawning effect of startup acquisitions and the underlying mechanism around employee preferences. Section 5 demonstrates the implications of spawning for the acquirer's long-run performance. Section 6 concludes with the study's key insights, managerial lessons, and questions for future research.

2 Theoretical Framework and Hypotheses

2.1 Background on Startup Acquisitions

Acquisitions of high-tech startups in the US have experienced a steady rise in the past several decades (See Figure 1). Several factors drive the demand for startup acquisitions. I broadly discuss the three – though not exhaustive – primary motivations behind why incumbent firms choose to acquire startup companies. First, buyers frequently acquire startup companies to eliminate nascent competitors. By construction, acquisitions of startup firms tilt the existing competitive landscape toward the acquirer (Gans and Stern 2000). In support of this view, several studies document that established firms acquire nascent targets with technologies that pose competitive threats, and subsequently shut down the target company, or its core product, following the buyout (Santos and Eisenhardt 2009; Cunningham, Ederer, and Ma 2017). Accordingly, the heightened M&A activity among industry incumbents has raised policy concerns around the anti-competitive effects of acquisitions on the entry and survival of new enterprises.[4]

Second, established firms commonly acquire startups to bring in a new source of technological innovation (c.f., Granstrand and Sjolander 1990; Puranam 2001). The "markets for ideas" allow incumbent firms to transact on the startup's stock of knowledge through, for example, patent licensing and transfers (Arora, Fosfuri, and Gambardella 2001). Relatedly, acquirers can effectively complement – or outright outsource – their R&D efforts by acquiring young firms that invest in risky technologies (Higgins and Rodriguez 2006; Kaplan and Lerner 2010). By bringing in the target firm's knowledge stock, the acquirer can exploit the opportunity to produce new innovations by recombining knowledge (Fleming 2001) shared between the two firms (Puranam and Srikanth 2007). Consistent with this view, the broader literature shows that M&A has a positive impact on the buyer's innovation output (Ahuja and Katila 2001; Sevilir and Tian 2012) especially when it shares a large technological overlap with the target firm (Bena and Li 2014).[5]

Lastly, a major motivation for acquisitions is the talent inside the target firm (c.f., Ouimet and Zarutskie 2016). Organization scholars have long recognized human capital as an important asset and thus a source of competitive advantage for firms (Hall 1993; Coff 1997; Acemoglu and Pischke 1998; Teece 2011). However, frictions in external labor markets often limit employers' ability to find, train, and retrain workers. In contrast, acquiring a firm, thereby transferring

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[4] Betsy Morria and Deepa Seetharaman, "The New Copycats: How Facebook Squashes Competition from Startups," *The Wall Street Journal*, August 9 2017, https://www.wsj.com/articles/the-new-copycats-how-facebook-squashes-competition-from-startups-1502293444 (Accessed August 1 2018).

[55] However, for the innovation output of the target firm, several studies including Kapoor and Lim (2007) and Seru (2014) show that M&A has a negative impact.

workers across internal capital markets, bypasses the common frictions in traditional labor markets (Tate and Yang 2016). Since the most valuable – if the not the only – asset of a startup firm is its human capital, acquiring a startup company serves as an alternative channel to capture new talent.

A recent phenomenon, particularly in the technology industry, highlights startup firms as a hotbed of talent. In particular, large technology companies such as Facebook and Cisco have received intense attention in the media for increasingly engaging in "acqui-hiring" – a process in which they buy out startup firms, jettison the core business, and retain the employees.[6] In a hand-collected sample of roughly 100 acqui-hires between 2009 and 2013, Chatterji and Patro (2014) show that the acquirer discontinues the startup's product in a vast majority of the cases. However, roughly 90% of the acquired engineers stay with their new employer for at least a year. This suggests that the acquirers strategically abandon the startup's core business and efficiently allocate the new workers across existing projects in the company. In other words, many startup acquisitions reflect cases in which the acquirer is chiefly interested in the talent.

2.2 Startup Acquisitions as a Hiring Strategy

Why might a firm choose to hire through startup acquisitions rather than the traditional labor market? Compared to conventional hiring, acquiring a team in a single transaction can be advantageous for three reasons. First, the startup team's productivity is easily observable prior to the acquisition. In other words, the acquirer can reduce the information asymmetry problem in hiring (c.f., Jovanovic 1979; Abraham and Farber 1987) by identifying and purchasing a team that has already proven to work together effectively.

Second, startup teams likely accumulate team-specific complementarities that disappear once the team is dissolved. For instance, Jaravel, Petkova, and Bell (2018) document team-specific capital among inventors. Specifically, the authors show that an inventor's long-run productivity suffers when her collaborator experiences a pre-mature death. Given the work culture that startups generally embody (Turco 2016; Corritore 2018), their workers plausibly also develop team-specific capital that leads to productivity gains. Moreover, team-specific complementarities may increase employee retention. Growing evidence on peer effects and "co-mobility" suggests that co-workers often prefer to work together (Marx and Timmermans 2017), meaning that they jointly influence one another's decision to stay with the firm. Therefore, wholly acquiring the team could lead to higher retention and productivity among the acquired employees.

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[6] Coyle and Polsky (2013) as well as Selby and Mayer (2013) provide conceptual discussions of the "acqui-hiring" phenomenon.

Third, it is difficult to infer an individual's level of contribution to a group's outcome. In other words, an outside firm may be limited in its ability to identify, and thus poach the best employees from a startup team. To illustrate this "metering problem," Alchian and Demsetz (1972) describe two men lifting a heavy cargo into a truck. By observing the total amount of cargo lifted each day, it is impossible to accurately determine each individual's contribution to the group-level output. As a result, without costly assessment of each worker, it would be difficult for an outside firm to identify and hire the top contributors. In parallel, the problem of moral hazard in teams limits an outsider's ability to select out the low quality workers; since only the joint output of the team can be observed, subpar contributors – as well as free-riders – often cannot be identified (Holmstrom 1982). Given the limitations in the ability to properly attribute team output to individual inputs, startup acquisitions may therefore generate efficiency gains in hiring by bringing in the entire team rather than a collection of individuals.

Moreover, the acquiring firm can enhance employee retention by offering stronger employment contracts upon the acquisition than they would with regular hires. New employment contracts for acquired workers commonly include both economic incentives and restrictive clauses designed to reinforce employee retention. Typically, employment contracts used in startup acquisitions offer equity incentives with a vesting schedule of three to four years, along with restrictive clauses like non-competition agreements.[7] Taken together, startup acquisitions provide several advantages as a hiring strategy – including contractual levers to increase worker retention – in comparison to conventional hiring.

2.3   Worker Choices and Preferences

Theory and Hypothesis Development

However, this hiring strategy poses a theoretical friction from the perspective of the employee. Unlike organic hires who *choose* to join the new employer on their own volition, acquired workers have limited to no discretion in their employer's ownership change. This is because, as highlighted by the PayPal anecdote, the target company's decision to be acquired is ultimately driven by a few major stakeholders, typically the founders and early investors.

In other words, most non-founding employees are excluded from the pre-acquisition talks regardless of their personal preferences for working at the presumed acquiring firm. In theory, the lack of worker agency in the organizational change may lead to poor matches between the acquired workers and the acquirer. While some may be indifferent to the involuntary transition, other acquired workers may resent the new employer. In turn, the mismatch of preferences could

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[7] See Coyle and Polsky (2013) for discussion on standard equity incentives used in startup acquisitions. Regarding non-compete agreements and startup acquisitions, see Schneid (2006) and Younge, Tong, and Fleming (2014).

result excessive turnover. This leads to *Hypothesis 1*: *Compared to observationally similar organic hires, acquired workers are more likely to leave the firm.*

This mismatch issue may be especially severe in the context of startup acquisitions because the target firm (startup) and the acquirer (established firm) are fundamentally different types of organizations. Among the many differences, a primary distinction between the two types is the corporate culture. Unlike established firms, startup organizations tend reinforce cultural values of openness and autonomy (Turco 2016; Corritore 2018). Relatedly, organizational structure is a key differentiator. While established firms exhibit increasing levels of bureaucracy as they age (Hannan and Freeman 1984; Sorensen 2007) and grow in size (Saxenian 1996), their younger counterparts generally possess a flatter organizational structure that reinforces execution over formal procedures (Slevin and Covin 1990).

In response to their inherent differences, workers endogenously sort into the startups versus established companies based on their personal preferences for employment. More specifically, workers who prefer risk-taking and challenging work environments tend to self-select into startups (Baron, Burton, and Hannan 1996; Roach and Sauermann 2015; Kim 2018). In contrast, individuals who value job security and employer reputation are more likely to join established companies (Kim 2018). This is consistent with the theory of compensating differentials, where individuals take a pay cut to join a firm that closely matches their preferred employment conditions (Rosen 1987; Sorkin 2018) such as autonomy for scientists (Stern 2004). Consequently, the inherent differences between startup employees and their counterparts at more senior firms – as reflected by the endogenous sorting – suggest that startup acquisitions could generate substantial mismatches in preferences.

Qualitative Evidence

In my interviews with several founders and early employees of startups that were eventually acquired, many of the respondents discussed the stark contrast between their original startup employer and the acquirer. A central theme emerged across the many acquisition experiences: because the acquirer is typically an older firm, its level of bureaucracy is antithetical to the common entrepreneurial emphasis on speedy execution and learning through experimentation (Ries 2011). A startup founder, reflecting on why he begrudgingly left the acquirer in just a year, corroborated the cultural disparity following the acquisition:

> It's really hard for an entrepreneur – a high-risk, high-speed type of individual – to settle into a methodical, decision-driven culture of meetings... and the slowness of a big company. (Interviewed on February 8th, 2018)

Even for large tech companies that aim to preserve and emphasize an entrepreneurial culture (e.g., Google and Amazon), the tradeoff between bureaucracy and speed was inevitable.

A former early employee of a startup, who came to a large technology firm through an acquisition in 2014, remarked:

> [Acquirer]'s internal processes, language, and rules took months to learn. More importantly, incentives are inverted at big firms. Big companies are process-oriented... and with so much invested and publicized, the priority is minimizing mistakes. Small companies are results-oriented, so we swing for the fences.
> (Interviewed on June 24th, 2016)

While many of the interviewees shared that they became frustrated with the organizational differences and promptly left the acquirer, others were less resentful of their new employer's culture. In fact, some of the acquired workers seemed to embrace the formal hierarchy as well as the job security that the acquirer provided. When asked about why some of his employees stayed while others left with him, a founder of an acquired startup commented:

> Employees who stayed behind with [Acquirer] were those who enjoyed the comfort and security... and slower pace of a large organization. Those who left – like me – are the type that wants to go make things happen fast... Another driver for leaving [Acquirer] was that, in a large organization, you no longer get to *own* a part of the product. But in a startup, you are responsible for a big feature of the product, whose first year is dependent on you to build and make it right.
> (Interviewed on May 31st, 2018)

In other words, startup employees are not uniform in their preferences for work environment. While some strongly prefer an entrepreneurial culture, others may desire a more formal and hierarchical organization. Therefore, there is likely a large variation in the preference mismatch that results when established firms acquire a startup. This degree of preference mismatch between the acquirer and the acquired employees may then determine the severity of turnover. This leads to *Hypothesis 2: Acquired workers who strongly prefer to work for startup employers ("high preference mismatch") are the most likely to leave the firm.*

2.4 Competitive Spawning

Consistent with the preference mismatch theory developed above, prior studies document the impact of M&A on increased turnover among the target firm's executives (Walsh 1988; Cannella and Hambrick 1993; Wulf and Singh 2011). Generally, employee exits – especially among key members like executives – are costly because of the loss of firm-specific intangibles such as knowledge (Castanias and Helfat 1991) and routines (Wezel, Cattani, and Pennings 2006).

However, the strategic cost of turnover – beyond the loss of human capital – is dependent on the *destinations* of the departures. While some departing employees could switch into

unrelated industries, others may join competitor or complementary firms. Therefore, the strategic implications of employee exits are likely shaped by which firms receive these workers. For example, using mobility patterns of patent attorneys, Somaya et al. (2008) document that employee exits to competitors are detrimental to the source firm's performance. However, the study also shows that departures to complementary firms (e.g., clients) lead to higher sales for the source firm as a result of the new social ties that are formed.

An alternative career path after leaving a firm is a starting a new venture. A growing literature on employee entrepreneurship illustrates that many workers go on to start their own firms. Many studies document the various antecedents of entrepreneurial spawning, including the social ties (Nanda and Sorensen 2010) and skills (Gompers, Lerner, and Scharfstein 2005) developed while working at the parent company.

Another principal driver of employee entrepreneurship is disagreements that occur inside organizations (Anton and Yao 1995; Klepper and Thompson 2010). Establishing the link between disagreements and spinoffs, Klepper (2007) explains that disagreements arise because the employer is unable to sufficiently recognize an employee's idea or ability. As a result, the contention leads the employee to pursue the idea outside the firm.

Similarly, acquisitions are rife with organizational disagreements for several reasons. First, the integration process in technology acquisitions is frequently discordant between the two firms (Haspeslagh and Jemison 1991; Puranam, Singh, and Zollo 2006). When deciding how to efficiently allocate resources inside the firm (Stein, 1997), new managers may create disagreements by neglecting and not committing sufficient resources to the acquired technology (Rajan and Zingales 1998; Hart and Holmstrom 2010). Moreover, the integration process in technology M&A presents a key tradeoff between coordination and autonomy: while an effective merging of the organizations requires coordination, doing so comes at the cost of autonomy for the target firm (Puranam and Srikanth 2007). The loss of autonomy could result in dissatisfaction among the new employees (Hambrick and Cannella 1993) and ultimately in voluntary departures (Ranft and Lord 2000).

Second, cultural clashes between the acquiring firm and the target firm are common (Van den Steen 2010), creating another source of organizational disagreements. This tension is likely more severe in startup acquisitions because the acquiring firm – typically an established organization – and the target startup noticeably differ in their organizational structures (Slevin and Covin 1990), cultures (Corritore 2018), and practices (Turco 2016). Taken together, the resulting organizational disagreement from the cultural clash and the integration process could frustrate the acquired employees, spurring them to leave and pursue their ideas outside the firm. This leads to Hypothesis 3: *Compared to observationally similar organic hires, acquired workers are more likely to spawn their own companies.*

Conditional on spawning, what kind of firms are departing employees likely to start? Especially in knowledge-intensive settings like legal services (Campbell et al. 2012) and high-tech industries (Burton, Sorensen, and Beckman 2002; Gompers, Lerner, and Scharfstein 2005;

Howard, Boeker, and Andrus 2015), the employee-entrepreneurship literature documents substantial knowledge spillovers from the parent firm to the spawned company. In other words, startup founders commonly leverage the resources and knowledge from their prior employer including technological know-how (Franco and Filson 2006), market-related knowledge (Klepper and Sleeper 2005), network of potential suppliers and customers (Burton, Sorensen, and Beckman 2002; Gompers, Lerner, and Scharfstein 2005), and organizational routines (Phillips 2002; Wezel, Cattani, and Pennings 2006).

Consequently, when leaving to start their own firms, employees from high-tech startup acquisitions are likely to leverage the knowledge from their prior employer. In line with knowledge spillovers, these new ventures could be disproportionately clustered in the same industry. This leads to Hypothesis 4: *Compared to observationally similar organic hires, acquired workers are more likely to spawn their own companies, especially in the same industry.*

While newly spawned companies can be complementors, they can also be competitors. For example, Campbell et al. (2012) argue that employee-entrepreneurship leads to greater competition that adversely influences the source firm's performance. This leads to Hypothesis 5: *The amount of spawning is negatively related to the acquirer's performance, especially if the new venture is in the same narrow industry.*

3 Data and Measurement

For this study, I use employee-employer matched data from the US Census Bureau to build a large sample of high-tech startup companies – and their workers – that are acquired between 1990 and 2011. Along with the acquired workers, I also identify the employees who join the acquiring firm as organic hires in the same year as the acquisition. This approach ensures that all employees are new to the firm, meaning that tenure at the firm is fixed to zero for both groups of workers. In addition, to make sure that the differences in retention outcomes are not endogenously driven by worker characteristics, I use a matching algorithm to find observationally equivalent organic hires for each acquired employee. Then I compare the mobility decision of acquired workers and organic hires in the first, second, and third year following the year of joining. The following section provides a detailed description of the construction of firm- and individual-level data, and the resulting final sample.

3.1 Identifying High-Tech Startups

While M&A activity covers many industries and different types of firms, this study focuses on high-tech startup targets for several reasons. First, in order to examine a setting where human capital – more so than tangible assets such as land and machinery – is a key asset to acquire, I restrict the sample of acquisition targets to startups. Startups are defined as firms

that are younger than ten years old, where the firm's birth year is the year when the first employee is hired.

Second, I focus on the high-tech sector in order to differentiate small businesses from high-growth startups. While many researchers and practitioners alike broadly use the term entrepreneurship, there are different forms of entrepreneurship . Most notably, small businesses and growth-oriented startups are two distinct types of entrepreneurship albeit both tend to consist of young firms. On the one hand, high-growth startups are a small subset of new firms that quickly scale and account for a disproportionately high share of job (Decker et al. 2014; Guzman and Stern 2016). On the other hand, small businesses tend to remain small because they typically do not have a desire to grow large or innovate in a meaningful way (Hurst and Pugsley 2011).

In the same way, acquisitions of young firms include both high-growth startups and small businesses. According to the M&A database constructed for this study (as further described in Section 3.2), acquisitions – whereby one firm is subsumed under the ownership of another existing firm – among young firms occur predominantly in the small business sector, most notably restaurants and dentist offices. As Figure 1 shows, roughly 85% of startup acquisitions take place in non-high tech industries. Therefore, given that the prevailing view on startup acquisitions concerns high-growth companies, it is critical to distinguish the two forms of entrepreneurship in this study.

To differentiate between high-growth startups and small businesses, many studies in the entrepreneurship literature limit their study to venture capital-backed startups or young firms that are granted a patent (Azoulay et al. 2018). Since venture capital financing and patenting are early firm outcomes – rather than innate traits of the firm – that endogenously reflect their underlying quality, this study does not use these markers in order to avoid selecting on firm quality.

Instead, I attempt to focus on high-growth startups by restricting the sample to high-tech startups. This approach has several advantages. First, the categorization of high-tech versus non-high-tech is a time-invariant measure that is determined at the time of the establishment's birth. Second, high-tech industries are objectively defined by the Bureau of Labor Statistics as the set of NAICS-4 industries with the highest share of STEM-oriented workers. Accordingly, I follow Hecker (2005) and Goldschlag and Miranda (2016) to define the high-tech sector.[8] While I impose the high-tech condition on the target startup firms, buyers can operate in any industry.

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[8] High-tech sectors in this study consist of: Semiconductor and Other Electronic Component Manufacturing; Pharmaceutical and Medicine Manufacturing; Data Processing, Hosting, and Related Services; Computer Systems Design and Related Services; Software Publishers; Information Services; Architectural, Engineering, and Related Services Scientific Research and Development Services; Computer and Peripheral Equipment Manufacturing; Navigational, Measuring, Electromedical, and Control; Aerospace Product and Parts Manufacturing; Communications Equipment Manufacturing; Telecommunications

3.2 Firm Characteristics

The Longitudinal Business Database (LBD) is the primary firm-level dataset in this study. The LBD is a panel dataset of all establishments in the U.S. with at least one paid employee. The LBD covers all industries in the private non-farm economy and every state in the US. The LBD begins in 1976 and currently runs through 2015. While the underlying observations are at the level of the establishment, the LBD assigns a unique firm identifier to each establishment. This is a useful feature especially for firms with multiple establishments. Furthermore, the longitudinal nature of the LBD allows researchers to identify the birth of startup companies and track important business characteristics including firm age, employment, payroll, and exit.

More importantly, I identify acquisitions in the LBD based on firm ownership changes. The main benefit of relying on the LBD for detecting M&A activity is the systematic coverage of young, private firms, for which standard M&A databases (e.g., SDC Thomson) are known to be limited in coverage. When a firm undergoes an acquisition, its firm-identifier changes to that of the surviving (parent) firm in the following year. I construct a set of firms that experience such change. In order to exclude non-M&A-based changes to firm ownership (e.g., false positives) such as divestitures and corporate restructuring, I leverage the pre-acquisition establishment-level name and EIN information to carefully validate the detected cases of acquisitions. In short, I rule out cases in which (1) the ex-ante names of the acquired and acquiring establishments are highly similar and (2) EINs do not change. Consequently, I build a comprehensive database of firm acquisitions in the LBD between 1985 and 2015. See Figure 1 for trends in startup acquisitions over time.

[Insert Figure 1 here]

3.3 Worker Characteristics

Worker-level information is based on the Longitudinal Employer-Household Dynamics (LEHD), which is an employee-employer matched dataset that covers 95% of private sector jobs. The study uses the full available version of the LEHD, which includes all US states except Massachusetts. The current LEHD time coverage spans from 1985 to 2014, although most states are not available before 2000 (See Figure 2 for a map of included states and their earliest year of coverage).[9] The LEHD tracks individuals at a quarterly basis and provides information on earnings, linked employer identifier, and demographic characteristics (e.g., age and gender). These quarterly worker-firm observations allow me to precisely determine whether and when acquired workers transition to the acquiring firm as well as their post-acquisition mobility decisions. Employers in the LEHD are observed at the state EIN level. I merge the LEHD to the LBD using the crosswalk developed by Haltiwanger et al. (2014).

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[9] States vary in their first time of entry in the LEHD data. The earliest entrant is Maryland in 1985Q2. Most states enter the data by 2000. See Vilhuber (2018) for a detailed description of the LEHD.

I use the earnings and join date information in the LEHD to categorize startup employees as founders, early joiners, or late joiners. Similar to Kerr and Kerr (2017) and Azoulay et al. (2018), I define founders as employees who join the firm in the first quarter of operation and are among the top three earners during the firm's first year. Relatedly, early joiners are those who join the firm in the first quarter but are not among the top three earners. Lastly, late joiners are those who join the firm after the first quarter.

One limitation of the worker-level data is the inability to distinguish voluntary separations and involuntary turnover. To ensure that retention outcomes are not driven by a large share of target firm's employees who are being fired upon the acquisition, I limit the acquired worker sample to those who work for the buyer for at least two quarters. This process eliminates about 10% of the target firm's workforce who – whether voluntarily or involuntarily – never join the acquiring firm. Presumably, all remaining workers received and accepted a job offer to work for the acquiring firm, mitigating the concerns around dismissed workers.

3.4 Final Sample

Beginning with the full set of acquisitions in the LBD, I identify roughly 6,000 cases in which high-tech startups are acquired. After matching to the LEHD and restricting to years between 1990 and 2011 to allow for at least three years of observation following the acquisition, the sample is reduced to 3,700 acquired startups.[10] On the worker side, there are 344,000 target employees who are acquired and transition to the buyer, along with 6.8 million workers who are conventionally hired at the buyer firm in the same year as the acquisition.

To ensure that the differences in retention outcomes are not driven by unobserved characteristics such as worker quality or seniority, each acquired worker is matched, using Coarsened Exact Matching (Iacus, King, and Porro 2012), to an observationally equivalent organic hire who joins the same buyer firm during the acquisition year. While worker roles are not observed in the LEHD, I use detailed worker characteristics – namely earnings, age, and gender in the year prior to the acquisition – to adjust for inherent differences in human capital between the two groups.[11] By conditioning the acquisition year to be the join year for organic hires, tenure at firm is mechanically set to zero for both the acquired workers and organic hires. Therefore, differences in retention outcomes in this study are not driven by differences in tenure. The final sample includes 3,700 startup acquisitions, 260,000 acquired workers, and 2.1 million regular hires. Tables 1A and 1B present the summary statistics of the final sample's firms (both the target and buyer) and their employees.

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[10] Several factors contribute to the reduction in sample size when matching LBD firms to the LEHD. First, because of the imperfect EIN-based matching between the two data sources, roughly 30% of the firms in the LBD are not found in the LBD-LEHD crosswalk. Second, Massachusetts is not included in the LEHD, meaning that the identified firm-level acquisition is dropped from the sample if the target or the acquiring firm is based in Massachusetts.

[11] In order to avoid partial annual earnings, I use "full quarter earnings" which are calculated as the wages in a quarter for which the person receives non-zero wages from the preceding and subsequent quarters.

3.5 Main Variables

Dependent Variables

The main dependent variables in this study are worker-level retention outcomes. $Depart_{ijt}$ is a binary outcome equal to 1 if worker i is no longer employed at the acquiring firm j in year t since the acquisition. The variable remains as 0 if the worker is employed at the firm for any amount of time during the year of interest. For example, if a worker acquired in 2005 leaves the firm in 2006, then the $Depart_{ij1}$ would equal 0 while $Depart_{ij2}$ would equal 1.

Similarly, $Spawn_{ijt}$ is a binary outcome equal to 1 if worker i in acquiring firm j is a founder of a new firm born by year t (See Section 3.2 for definition of founders). Similarly, $Related\_Spawn_{ijt}$ is a binary outcome equal to 1 if worker i is a founder of a new firm – residing in the same 2-digit NAICs industry as the original target firm – born by year t.

To measure acquirers' post-acquisition performance, I use employment- and revenues-based growth measures. The growth measures are based on a three-year window where the initial year is the year of the acquisition.[12] The growth rate between year t and $t+3$ is calculated as $\frac{Y_{jt+3} - Y_{jt}}{(Y_{jt+3} + Y_{jt})/2}$, where Y_{jt} is acquirer j's employment or revenues in year t. This is a standard measure in the firm dynamics literature – known as the Davis-Haltiwanger-Schuh (DHS) growth rate (Davis et al. 1996) – that weights the rate of growth by firm size. In doing this, this measure minimizes the naturally negative relationship between initial size and growth.

Independent Variable

At the worker-level, the primary independent variable is $Acquired_{ij}$, which is a dummy variable equal to 1 if worker i in acquiring firm j is hired through a startup acquisition, and 0 if the worker is organically hired. For each acquisition, *Number of Spawned Companies* is a firm-level count of startups spawned by the acquired workers within three years since the acquisition.

3.6 Measuring Preferences for Startup Employers

Following Section 2.3, the main challenge of testing the impact of worker preferences on turnover is the empirical measurement of preferences. In particular, the variable of interest is the level of individual preferences for a startup versus an established employer. While workers' employment preferences are not directly observed in the data, I exploit their firm's regular turnover events – in particular, employer-to-employer flows – using a revealed preference argument.[13,14] A departing employee's intentional choice to join a startup, rather than an incumbent firm, reveals her preferences for employment conditions. For each target firm, I

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[12] Robustness checks using a 5-year window are available.

[13] Haltiwanger et al. (2012) show that turnover is commonly high at young firms (1-10 years old): in a given quarter, roughly 25% of the workforce separates from their young employer, while separations at older firms is around 15%.

[14] In my data, the average target firm exhibits 160 employee separations in its lifetime prior to the acquisition.

aggregate these choice patterns to systematically derive a peer-based proxy for employer preferences.

Conceptually, two central ideas lay the foundation for using peer turnover patterns to proxy for co-workers' employer preferences. First, job transitions are intentional choices that reflect employees' preferences for employer's characteristics. Simply put, a worker's decision to join a particular firm – and thereby *not* join another employer – demonstrates her relative valuation of the two firms based on both pecuniary and non-pecuniary factors (Sorkin 2018). A substantial body of work in labor economics demonstrates that workers choose to join certain firms based on preferences – effectively paying for such amenities in the form of a wage discount (c.f., Rosen 1987; Stern 2004; Sorkin 2018). When aggregated up, these mobility choices characterize the target firm's average preference for startups relative to established firms.[15]

Second, job transitions by former colleagues are especially relevant because they resemble the behavior of the acquired startup employees. Since both the acquired and former employees initially selected into joining a particular startup rather than other potential employers, these workers likely exhibit similar preferences for employment. This premise is supported by the evidence that workers differentially select into startups versus established firms based on their personal preferences. For instance, individuals who desire autonomy and risky work (Baron, Burton, and Hannan 1996; Roach and Sauermann 2015; Kim 2018) tend to sort into entrepreneurial companies. Therefore, by leveraging the insight that a group of workers all initially selected to join the same startup, I leverage the choice patterns of former co-workers to build a peer-based proxy for employer preferences.

To construct this measure, I track the departures of the target startup's employees *prior* to the acquisitions along with their destinations. Using the LEHD to track their career histories, I find roughly 1 million employer-to-employer transitions – before the acquisition – among the employees of the target firms. These former colleagues do not directly influence the behavior of the acquired employees because they are not present at the time of the acquisition. Thus, their decisions to join a young firm or an established company are exogenous to the later acquired workers' choice of departing or staying with the buyer firm. Mechanically, I aggregate all of the pre-acquisition mobility decisions, and then calculate the share of transitions to other startups versus old firms.[16] The resulting firm-level shares characterize and therefore proxy for how strongly the target firm's employees prefer to work for startup employers.[17]

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[15] In the Appendix, I directly test whether the share of departures is a close proxy for startup preferences, rather than a measure driven by other firm characteristics. Specifically, I show that firm covariates (age, size, and industry) do not systematically predict the share of pre-acquisition departures to startups. For further robustness, I use the residuals from these regressions to substitute for the actual startup shares in the analysis.

[16] For this measure, a startup is defined firms that are younger than five years old. All results are consistent when defining startups as younger than ten years old.

[17] One limitation of this measurement based on workplace peers is that preferences are measured at the firm, and not individual, level. Therefore, it does not allow for within-firm variation in the preference for startup employers.

Figure 3 illustrates the distribution of the target firms and their pre-acquisition share of departures to startups. The distribution of the acquiring firms is also shown to provide a benchmark for older firms and their share of employee departures to startups. These kernel densities suggest that, even among the young acquired startups, there is a significant variation in the share of departures to young vs. old employers. Relative to that of the acquiring firms, the curve for the target firms is shifted to the right, meaning that workers at young firms unsurprisingly tend to flow to other young firms.

[Insert Figure 3 here]

4 Empirical Results

4.1 Econometric Framework

The main results in this study are based on a series of linear worker-level regressions. These regressions are a variation of the following simple econometric framework with worker i in buyer firm j:

$$Y_{ij} = \beta_0 + \beta_1 Acquired_{ij} + \delta_j + \varepsilon_{ij} \tag{1}$$

Y_{ij} is a set of binary outcome variables including departing from firm j by year k since the acquisition, where $k \in \{1,2,3\}$. Other dependent variables – namely, spawning and related spawning in year k – are similarly constructed as binary outcomes that are used in additional regression specifications. Furthermore, δ_j is the target-buyer firm fixed effects, meaning that all firm-specific traits including industry, geography, and year of the acquisition are subsumed by these parameters. In other words, workers who are acquired by firm j are solely compared to those who join firm j as organic hires during the same year as the acquisition.

It is important to note why linear (ordinary least squares) regression models are used instead of non-linear models (e.g., probit, logit) given that the dependent variables are binary outcomes. While probit and logit models have the benefit of bounding the estimates between 0 and 1, the resulting estimates may be biased due to the incidental parameters problem. Unlike linear regressions that provide the best linear approximation to the conditional expectation function, logit and probit models may produce biased estimates as the number of parameters grows relative to the number of observations.[18] This issue may be particularly problematic when including many fixed effects in the regression.

Firm fixed effects δ_j in Equation (1) are crucial in this empirical design because they allow β_1 to be interpreted as within-firm effects. In other words, estimates of β_1 identify the effect of being acquired versus hired on the worker's likelihood of exiting the firm, after accounting for

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[18] See Angrist and Pischke (2009) for a detailed discussion on limited dependent variables (e.g., binary), non-linear models, and the incidental parameter problem.

firm-specific effects including region, industry, and join year. Therefore, the inclusion of δ_j mitigates the endogeneity concerns that would arise when comparing across firms with both observable and unobservable differences. Given the importance of firm fixed effects as the identification strategy in this empirical framework, this study uses a linear probability model in order to avoid the incidental parameters problem.

4.2 Post-Acquisition Employee Departures

Figure 4 shows the unconditional rates of employee retention for acquired workers versus organic hires. Since the set of acquired workers in the sample are those who work for the buyer for at least two quarters, retention rates are mechanically set to 100% in the year of the acquisition. In the following years, acquired workers noticeably exhibit lower retention rates. While 88% of the regular joiners are retained by the year after the join (acquisition) year, the rate for acquired workers is 67%. However, the stark differences in retention rates appear to wane over time.

[Insert Figure 4 here]

In parallel to Figure 4, Table 2 presents the linear probability regression estimates on employee retention, accounting for individual and firm characteristics. The dependent variable is a binary indicator that equals 1 if the employee leaves the acquiring firm by year k. All specification include target-acquirer firm fixed effects. While the first three specifications include all workers, the latter three specifications include only the workers that are closely matched in earnings, age, and gender. As a result, acquired workers and traditional hires in the matched specifications are observationally equivalent with regards to key human capital characteristics. Nonetheless, results are consistent with and without matching, suggesting that retention outcomes are not explained by innate individual characteristics.

Overall, all specifications indicate that acquired workers are significantly more likely to leave the acquirer. The effect ranges from 8 to 21 percentage points and is statistically significant at the 1% level. While only 12% of the comparable regular hires leave the firm in the first year after the acquisition, 33% of the acquired workers leave in the same time period. In a three-year window, acquired workers are approximately 15% more likely to leave the firm relative to regular hires. Therefore, even after controlling for important worker traits such as earnings and age, acquired workers exhibit greater turnover relative to organic hires.

[Insert Table 2 here]

It is important to note that the differences in retention between the groups become much smaller over time. This is consistent with the view that the elevated rates of turnover among acquired workers is largely driven by the underlying worker-firm match quality. Following the the Jovanovic (1979) model of worker tenure and turnover, acquired workers who learn that they are a good match tend to stay with their new employer. Consequently, rates of employee exits among the two groups appear to converge over time. Taken together, these results imply

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that new employees learn about the quality of their match with the firm relatively quickly, as reflected by the large share of employee outflows in merely the first year of employment.

4.3   Mechanism: Preference Mismatch

In this section, I investigate preference mismatch as the mechanism that explains the greater turnover among acquired employees in comparison to regular joiners. Put differently, I assess whether acquired workers who prefer to work for startup employers are more likely to leave after they are acquired. Since acquiring firms tend to be larger and older than targets, strong preferences for startup employers imply a greater degree of preference mismatch between the acquired workers and the acquiring firm. To test these predictions, I use the firm-level proxy for startup preferences developed in Section 3.5: the share of pre-acquisition departures to young firms. For simplicity, this variable is henceforth labeled *Startup Preference Scores*.

Figure 5 depicts the unconditional rates of employee departures by *Startup Preference Scores* quartiles, where Q1 represents the set with the lowest preference for startup employers. For all three years following the acquisition, the rate of employee exits are generally increasing in *Startup Preference Score*. In other words, target firms that demonstrate higher shares of departures to startups are more likely to demonstrate post-acquisition turnover.

[Insert Figure 5 here]

Table 3 is the regression counterpart to Figure 5. This set of regressions is identical to that in Table 2, but with interaction terms between the acquired worker dummy and the startup preference quartiles. The omitted group is *Acquired x Startup Preference[Q1]*. Therefore, the regression estimates corresponding to the interaction terms indicate the marginal effect relative to the omitted group.

[Insert Table 3 here]

The row corresponding to the highest *Startup Preference Score* (Q4) demonstrates the highest rate of turnover. Relative to the acquired workers in the lowest quartile, workers in this category are roughly 9 percentage points more likely to leave the acquirer in three years. Consistent with the trends in Figure 5, the subsequent rows are also positive, albeit smaller in magnitude. While some estimates are statistically indistinguishable from zero, the highest quartiles – Q3 and Q4 – are always positive and significant, implying that those who strongly prefer to work for startups are the most likely to exit. These results confirm Hypothesis 2.

4.4   Post-Acquisition Employee Spawning

Next, I test the hypothesis that acquired workers are not only more likely to leave, but also more likely to start their own companies upon leaving. Similar to Section 4.2, I empirically test this prediction using a series of cross-sectional regressions with a binary dependent variable

Spawn$_{ijk}$ that equals one if the worker i in acquiring firm j is a founder of a new firm by year k following the acquisition. Specifications 1-3 in Table 4 exhibit the resulting regression estimates.

[Insert Table 4 here]

As in the case of employee departures, acquired workers are roughly 0.3 percentage points more likely to launch their own ventures relative to organic hires. In all specifications, this effect is positive and statistically significant at the 1% level. Although employee spawning is a rare outcome[19], meaning that the absolute size of the effect is seemingly small, the economic magnitudes are substantial in relative terms. Compared to regular hires, acquired workers are 80% more likely to enter into entrepreneurship within two years of being acquired. Thus, Hypothesis 3 is empirically supported.

Unlike the results on employee departures, the relative effects on employee spawning do not decline over time. This is likely due to the lag between leaving an employer and starting one's own company, especially since firm birth is measured as the year that the first employee is hired. For example, an acquired worker who realizes a poor match with his employer may leave in the first year, subsequently gather the necessary resources to start his own firm, and eventually hire the first employee the second or third year following the acquisition. Therefore, it is not surprising that the impact of acquisitions on employee spawning – unlike that on employee departures – does not monotonically decline over time.

Moreover, I investigate whether the spawning effect demonstrates knowledge flows from the original target firm to the new venture. In other words, I test whether entrepreneurial entry following startup acquisitions disproportionately occur in the same industry as the target firm. Same-industry spawning would reflect knowledge flows from the original target to the new venture. Accordingly, results on related spawning are shown in Specifications 4-6, where the dependent variable is a series of binary outcomes equalling one if the worker founds a new firm in the same industry – defined at the two-digit NAICS level – as the target firm.

The estimates range from .08 to .23 percentage points in the first and third year following the acquisition, respectively, and are all significant at the 1% level. Considering that related spawning is a very rare outcome, the economic magnitudes are substantial: By the second year following the acquisition, acquired workers are roughly 100% more likely to launch a company in the same industry relative to organic hires. Therefore, Hypothesis 4 is confirmed: acquired workers are not only more likely to become entrepreneurs, but also more likely to start companies in the same space as their former employer.

4.5   Firm Performance and Competitive Spawning

How does post-acquisition spawning, especially when occurring in the same industry, affect the acquirer's long-run firm performance? While acquisition-induced entrants born in the same

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[19] About 0.3% of the acquired workers spawn their own company within three years of the acquisition.

industry can be complementary firms that provide network and trading benefits to the source firm, they can also be new competitors. I analyze the impact of new ventures founded by acquired employees by turning to the following firm-level regressions for acquiring firm j in industry k, state s, year of acquisition t:

$$Growth_{jt+3} = \alpha_0 + \alpha_1 Count\_Spawn_{jt+3} + \gamma_{kt} + \tau_s + X'_j\Theta + \varepsilon_{ij} \tag{2}$$

The dependent variable $Growth_{jt+3}$ is the acquiring firm's DHS rate of growth between year t and $t+3$, measured in employment as well as revenues (See Section 3.4 for more on DHS growth rates). To account for industry-specific trends, which also may vary with time trends, acquisition year-industry interacted fixed effects γ_{kt} are included.[20] Since the underlying sample contains roughly 3,500 firms, the interacted year-industry fixed effects are defined at the 2-digit NAICS level in order to allow for sufficient number of observations in each of the estimated bins. Moreover, state fixed effects τ_s, defined by the location of the acquiring firm's headquarters, are included to absorb geographic trends that may affect firm performance. A vector of buyer firm traits X_j controls for firm age as a series of four dummy variables for each of the acquirer firm age quartiles.

Table 5 presents the firm performance regressions. Panel A uses employment growth while Panel B uses revenue growth.[21] The first specification in both panels counts the number of companies spawned – outside the original target firm's two-digit NAICS industry – by the acquired workers by year three since the acquisition. The subsequent specifications count the number of companies spawned by the acquired workers in the same industry. The degree of industry similarity between the original target company and spawned firm becomes higher across the specifications from two- to four- to six-digit NAICS industries.

[Insert Table 5 here]

In both panels, Specification 1A shows that spawning in unrelated industry has a negative, albeit small, impact on the acquirer's performance. Relative to the acquirers that do not experience any unrelated spawning within three years of the acquisition, an entry of one unrelated spawned entrant is associated with a 1.6% lower rate of employment growth within the three-year window. These modest effects likely reflect the cost associated with general employee turnover (e.g., replacement cost) independent of competitive spawning.

However, the negative effect is substantially larger in Specification 2A that counts the number of related spawning in the same NAICS-2 industry following the acquisition. An additional company founded in the same NAICS-2 industry is linked to a 2.5% (2.0%) decrease in long-run employment (revenue) growth. Moreover, the negative impact grows even larger as

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[20] In the LBD, NAICS industry is defined at the establishment level. For firms with multiple establishments, I determine the firm's dominant NAICS-2 industry as the one with the highest share of the firm's employment. Within this dominant NAICS-2 industry, I again use employment shares to determine the dominant NAICS-3 industry. This process is repeated until the level of six-digit NAICS industry.

[21] Given the limited coverage of firms and their revenue information in the LBD, especially among young firms, the observation count is noticeably lower than when using employment growth.

the industry similarity becomes narrower.[22] For instance, as shown in Specification 4A, one spawned company in the same NAICS-6 industry, which is the most granular industry level, is associated with a 3.5% decline in employment growth. All of these results are statistically significant mostly at either the 1% or 5% levels, and the findings based on employment are strongly consistent with those using revenues.

It is worth mentioning the firm-level analyses in Table 5 is subject to endogeneity concerns. For example, industry lifecycles could be a credible alternative explanation: Acquirers operating in industries in a time with heavy entry rates may both see declines in performance due to competition and experience a rate of post-acquisition spawning. To account for this possibility, Specifications 1B, 2B, 3B, and 4B in Table 5 directly control for industry-year-specific entry dynamics. In particular, these specifications include a variable that counts the number of new entrants during the acquisition year t in the same industry, where industry is defined at the level of the corresponding column (e.g., 2-digit NAICS industry in Specifications 1B and 2B; 4-digit NAICS industry in Specification 3B). Results are strongly consistent with the earlier results of Table 5.

Despite the limitations from other potential omitted variable bias, these persistently strong results suggest a negative relationship between post-acquisition spawning among the acquired employees and firm performance. This view is corroborated by the fact that this negative correlation grows larger as the industry similarity between the entrants and the acquirer becomes more narrowly defined. Taken together, these findings suggest that employee departures following an acquisition can lead to the creation of new competitors that impair the buyer's long-run performance.

5 Conclusion

While a vast literature in entrepreneurship examines the birth and growth of new enterprises in isolation, several studies have demonstrated a rich interaction between young firms and industry incumbents – whether in a competitive or cooperative context (c.f., Gans and Stern 2003). This study sheds light on a growing trend that dynamically shapes the competitive landscape between nascent and incumbent firms: Startup acquisitions. Among other factors, a common motivation behind buying out startup firms is the desire to bring in superior talent.

This paper provides the first, large-scale empirical investigation on the efficacy of startup acquisitions as a hiring strategy versus conventional hiring. The fundamental takeaway is that acquired workers are significantly less likely to be retained in comparison to traditional hires, even after accounting for worker and firm-specific traits that may influence retention outcomes.

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[22] NAICS industry categorization ranges from two (broadest) to six (narrowest) digits. Narrower NAICS industries are subsets of broader NAICS industries.

At the core of this departure effect is the lack of agency for the acquired workers: unlike regular hires who choose to join a new employer, acquired workers seldom have a choice in their employer's ownership change. Therefore, precisely because the target employees do not choose their new employer, acquisitions often create poor matches between the target workers and the acquiring firm. As a result, those with a preference mismatch following the acquisition are predicted to exit the firm at a greater rate. In support of this theory, robust evidence indicates that the departure effect is strongest among target firms whose employees prefer to work for startup companies. Taken together, the central lesson is that worker choices matter: Because choices reflect their underlying preferences, workers who are able to voluntarily choose their new employer systematically tend to exhibit greater attachment to it.

Moreover, this study shows that, upon leaving, acquired workers are noticeably more likely to launch their own firms. These new ventures are disproportionately in the same industry as the original target firm, and appear to exert competitive pressures on the acquiring firm. As a result, managers at acquiring firms ought to place greater focus on assessing the retention likelihood of potential targets by better understanding the workers' preference to work for entrepreneurial rather than established employers – over and above the economic incentives that are designed to encourage the employees to stay. Attention on employee retention through the lens of individual preferences is likely to shift not only the overall rate of employee turnover, but also the ensuing competitive landscape partly shaped by acquisition-induced entrants.

There are several limitations to this study worth highlighting. First, the proxy for startup preferences developed in this study solely operates at the firm-level. The ideal measurement is a survey of individuals and how strongly each individual personally prefers to work for large versus small organizations. However, to leverage the exogenous information generated from their co-workers' mobility patterns, the proposed measure calculates the startup preference score at the firm-level. Therefore, this study is unable to capture the within-firm variation in individuals' employer preferences.

Second, the LEHD does not distinguish voluntary from involuntary turnover. While this study puts forth a narrative around voluntary departures driven by worker preferences, many employees at the target firm may simply be fired. Unfortunately, the data do not allow for careful distinction between the two types of departures. However, to mitigate this potential issue, I take two concrete steps in the analysis. First, I restrict my sample of acquired workers to those who work for the buyer at least two quarters, meaning that they initially receive job offers for employment at the acquirer. That is, these workers are not outright dismissed upon the acquisition. Second, I check whether acquired workers who leave are systematically more likely to enter into unemployment relative to regular joiners who leave. The intuition is that higher unemployment rates among acquired workers would validate the concern around involuntary dismissals. Fortunately, the two groups do not appear to show major differences in the propensity for unemployment upon leaving the acquirer.

This study concludes by highlighting a few areas for future research. For instance, a key remaining question is how the price of startup acquisitions – which frequently surpass a billion dollar valuation in spite of the uncertainties associated with new markets and technologies – accounts for the post-acquisition retention patterns of the target workers. Put differently: What is the price of (retained) entrepreneurial talent? Although acquirers may rationally price their transactions by accurately predicting the likelihood of preserving the human capital, it could be the case that acquirers systematically overpay in light of the elevated turnover documented in this study.

Another avenue is to explore how the acquired technology is integrated and implemented inside the buyer firm. Extending a broad literature on this topic (c.f., Puranam and Srikanth 2007; Bena and Li 2014), a novel topic is the duality of technology and individuals that flow during an acquisition. Given that startup acquisitions are an empirical setting in which there is co-mobility of patents and individuals – including cases when one asset moves but not the other – the complementarity between knowledge and individuals can be empirically assessed. In other words, how useful is knowledge without the original source? Insofar as knowledge and talent are valuable assets for firms, this seems to be a first-order line of scholarly inquiry. More broadly, the increasingly popular use of comprehensive employee-employer datasets is promising for future research streams on how human capital not only shapes the creation and growth of new ventures, but also how incumbent firms can acquire such entrepreneurial talent.

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Figures

**Figure 1**: Time Trends in US Startup Acquisitions
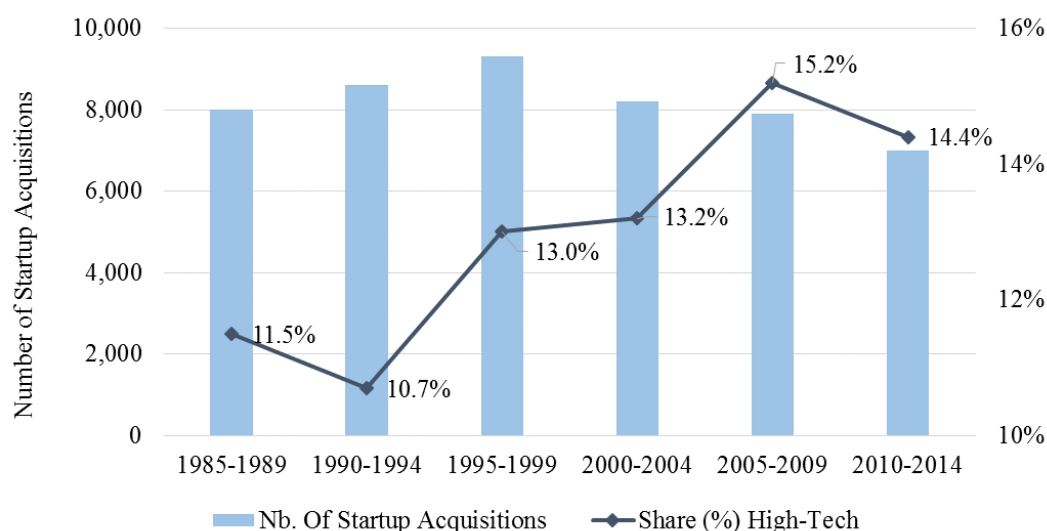
Note: This figure counts the number of times that startups, defined as younger than ten years old, are acquired by existing firms in a given five-year window. Acquisition activity is measured using the author's algorithm based on firm ownership changes in the LBD. Share of high-tech is the percentage of startup acquisitions that occur in industries with the highest shares of STEM-oriented workers (See Section 3 for detailed description of defining high-tech industry).

Figure 2: Map of US States and Entry Year in LEHD
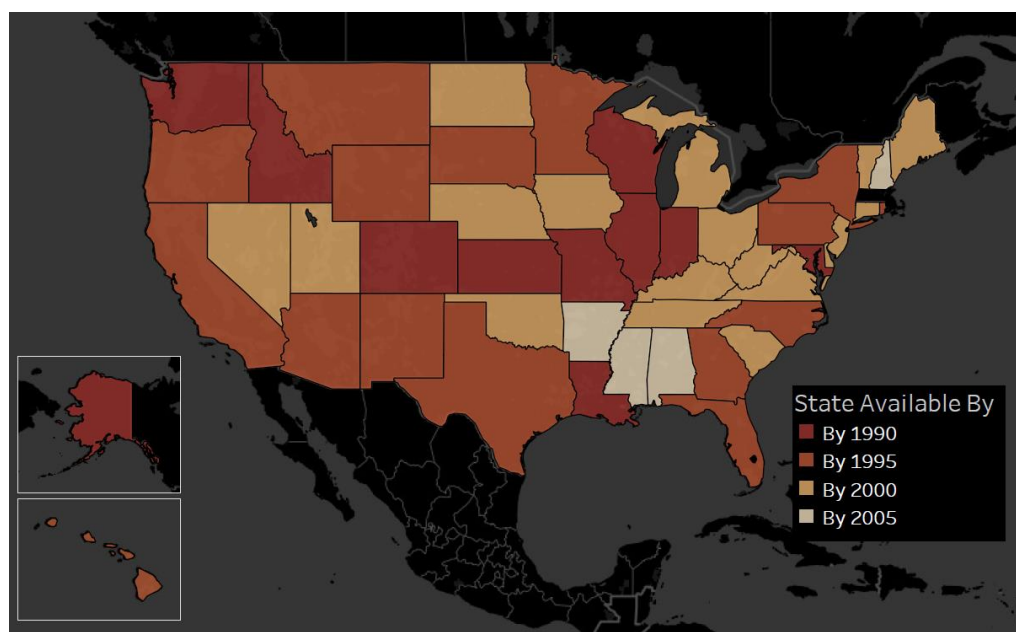
Note: See Vilhuber (2018) for a detailed description of the LEHD. This study uses all available states in the LEHD.

**Figure 3**: Distribution of Pre-Acquisition Departures to Startups
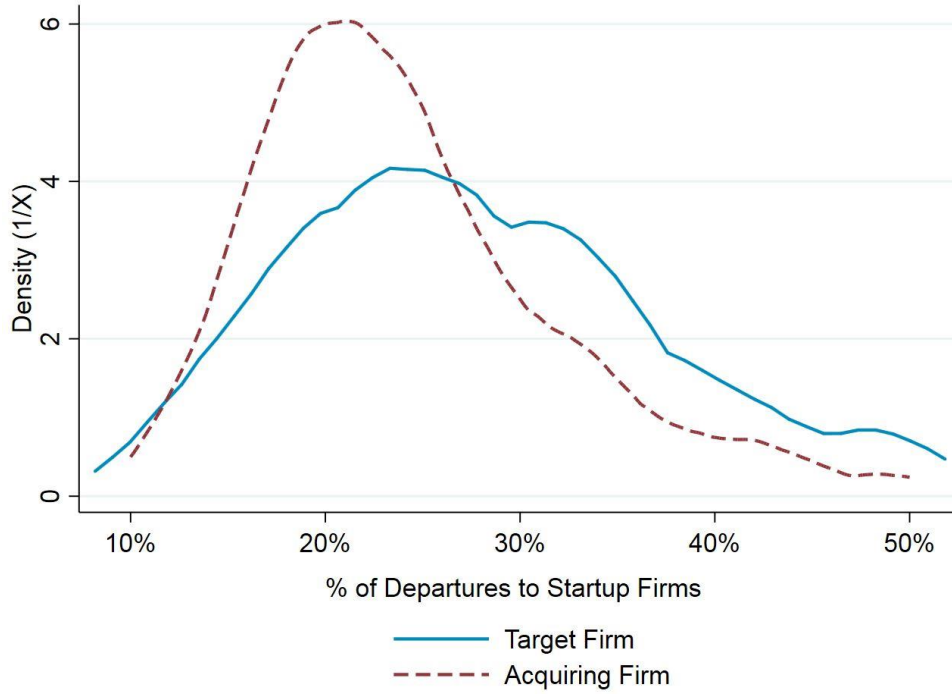
Note: This figure is the kernel density plot of the firm-level share of pre-acquisition employee departures to startup firms (5 years old or younger). Since the age of the receiving firm is the variable of interest, only employer-to-employer flows are counted.

Figure 4: Unconditional Rates of Employee Retention: Acquired Workers vs. Regular Hires
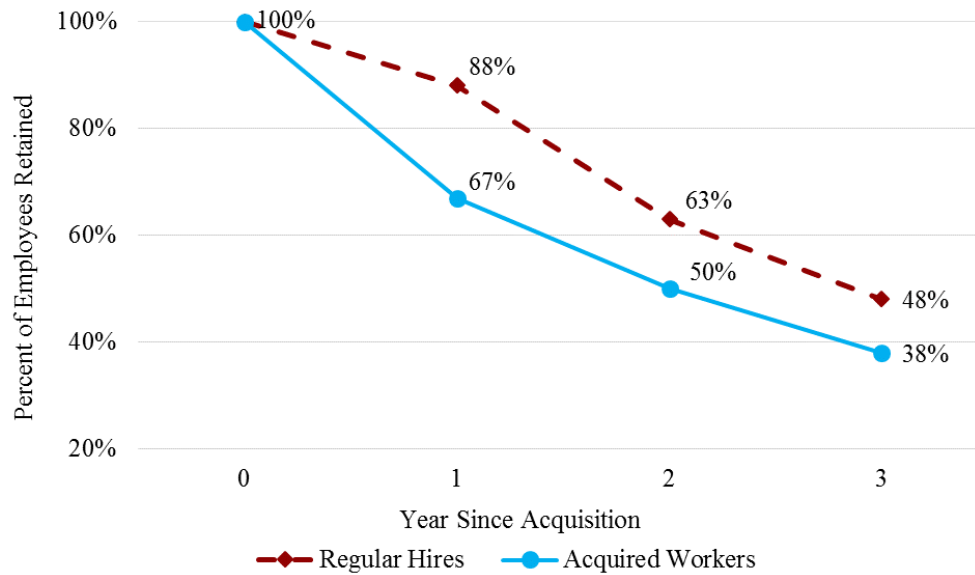
Note: This figure plots the non-parametric retention rates. Both acquired workers and regular hires join the acquiring firm in year 0. Employee is retained in year t if she works for the firm for at least a quarter in year t.

Figure 5: Employee Exit Rates by Startup Preference Score (Quartile)

Panel A: Employee Departures   **Panel B: Employee Spawning**
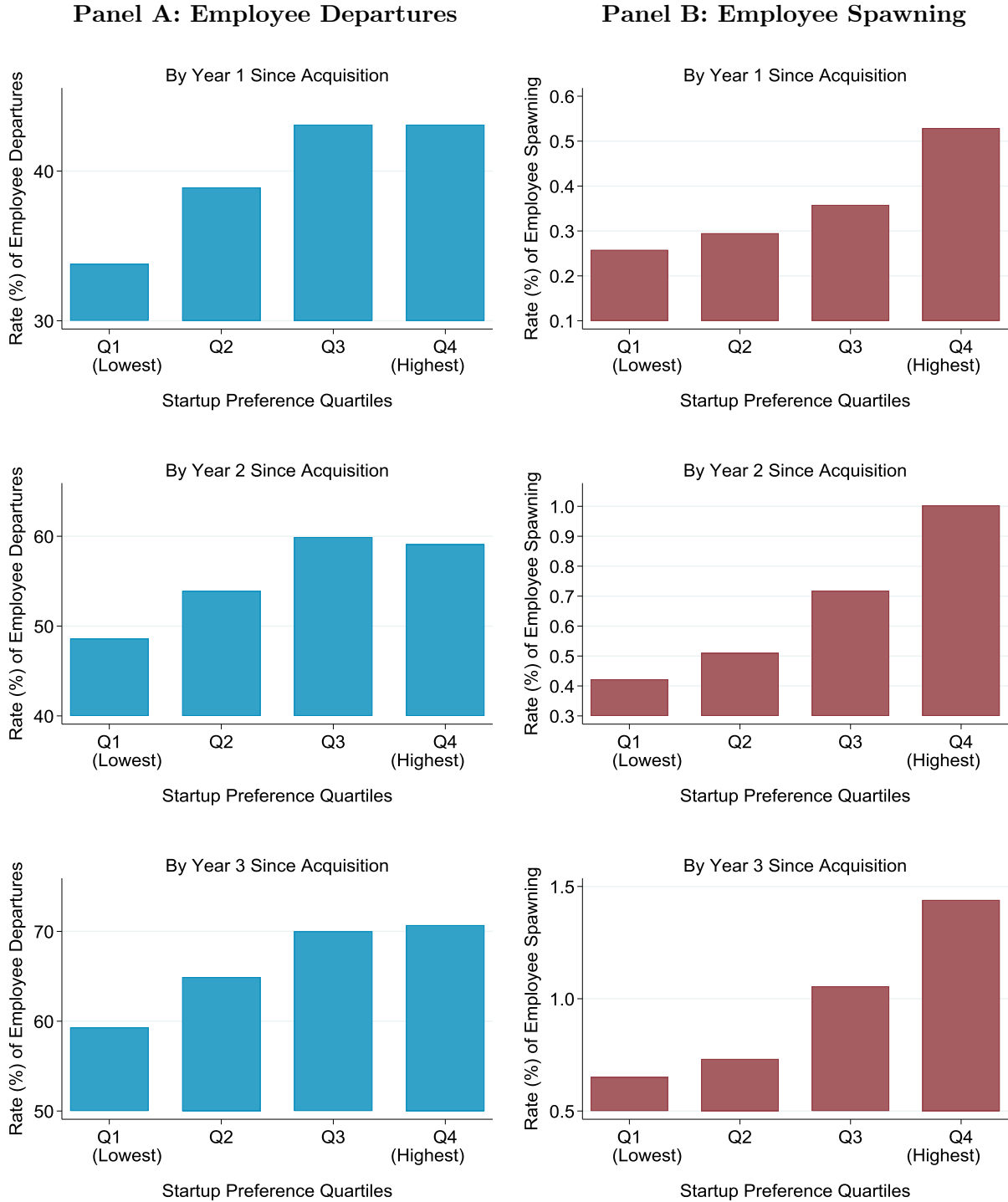
Note: These figures plot the unconditional rates of employee departures in Panel A and employee spawning in Panel B, respectively. X-axis is the quartile-indicator for the underlying target firm's share (%) of pre-acquisition worker departures to startups (5 years old or younger). Only acquired workers are included in measuring employee outcomes. Employee departure in year t equals 1 if she does not receive any wages from the firm in year t. Employee spawning in year t equals 1 if she is a founder of a new firm in year t.

Tables

Table 1A: Firm-level Summary Statistics

Characteristics	**Target Firm** N=3,700			**Acquirer**		
	Mean	**Median***	**SD**	**Mean**	**Median***	**SD**
Firm Size (Employee Count)	150	42	460	12,500	1,900	31,100
Firm Age	4.1	4.0	2.9	22.4	23.0	8.6
Payroll ($M)	10	3	30	860	130	2,700
Top NAICS-4 Industries (%)						
Computer Systems Design And Services	0.20		0.40	0.08		0.27
Mgmt., Scientific, and Technical Consulting Svcs.	0.12		0.32	0.02		0.15
Architectural, Engineering, and Related Services	0.11		0.31	0.06		0.24
Scientific R&D Services	0.07		0.26	0.03		0.16
Professional and Commercial Equipment & Supplies	0.07		0.26	0.05		0.22
Software	0.06		0.24	0.05		0.21
Data Processing, Hosting, and Related Services	0.06		0.24	0.03		0.17

Note: Following Census disclosure rules, quasi-medians (the average of observations in between the 41st and 59th percentile values) are shown.

Table 1B: Worker-level Summary Statistics

Panel A: Before Matching

Characteristics	**Acquired Workers (N=344,000)**			**Regular Hires (N=6,806,000)**		
	Mean	**Median***	**SD**	**Mean**	**Median***	**SD**
Annual Earnings ($)	86,700	56,600	1,006,000	69,100	46,900	173,000
Age	39.2	37.9	10.5	36.8	34.9	11.1
Male (%)	0.65		0.47	0.61		0.48

Panel B: After Matching

Characteristics	**Acquired Workers (N=260,000)**			**Regular Hires (N=2,094,000)**		
	Mean	**Median***	**SD**	**Mean**	**Median***	**SD**
Annual Earnings ($)	82,600	58,100	326,000	78,200	59,300	159,000
Age	38.1	37.4	9.8	36.5	35.5	9.5
Male (%)	0.67		0.47	0.69		0.46
Employee Type (%)						
Founder	0.01					
Early Joiner	0.12					
Late Joiner	0.87					

Note: Following Census disclosure rules, quasi-medians (the average of observations in between the 41st and 59th percentile values) are shown.

Table 2: Linear Regressions on Employee Departures: Acquired Workers vs. Regular Hires

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Depart by t+1	Depart by t+2	Depart by t+3	Depart by t+1	Depart by t+2	Depart by t+3
Sample	*Full*	*Full*	*Full*	*Matched*	*Matched*	*Matched*
Acquired Worker	0.2124***	0.1276***	0.0817***	0.2124***	0.1330***	0.0871***
	(0.0119)	(0.0123)	(0.0118)	(0.0134)	(0.0138)	(0.0133)
Mean DV of Control Group (Regular Hires)	**0.120**	**0.368**	**0.524**	**0.107**	**0.345**	**0.510**
Buyer-Target Firm FE	YES	YES	YES	YES	YES	YES
Observations	7,150,000	7,150,000	7,150,000	2,354,000	2,354,000	2,354,000
R-squared	0.1048	0.1145	0.1132	0.1132	0.1095	0.1150

Note: This table is a set of worker-level regressions using OLS. Specifications 4-6 are based on matched workers using Coarsened Exact Matching. Depart by k equals 1 if the worker does not receive any wages from the firm in year k. Standard errors, clustered at the firm level, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Linear Regressions on Employee Departures by Startup Preference

	(1)	(2)	(3)
Dependent Variable	Departure	Departure	Departure
Time Window	by *t+1*	by *t+2*	by *t+3*
Startup Preference[Q4] x Acq.	0.0902**	0.1138**	0.1136**
	(0.0419)	(0.0448)	(0.0464)
Startup Preference[Q3] x Acq.	0.0937**	0.1004**	0.0772*
	(0.0442)	(0.0452)	(0.0453)
Startup Preference[Q2] x Acq.	0.0278	0.0263	0.0377
	(0.0412)	(0.0438)	(0.0452)
Acquired Worker	0.1624***	0.0765*	0.0323
	(0.0366)	(0.0394)	(0.0417)
Mean DV of Regular Hires	**0.109**	**0.349**	**0.514**
Matched Workers	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES
Observations	2,354,000	2,354,000	2,354,000
R-squared	0.1141	0.1100	0.1144

Note: This table is a set of worker-level regressions using OLS. All specifications are based on matched workers using Coarsened Exact Matching. Depart by k equals 1 if the worker does not receive any wages from the firm in year k. Startup Preference[Qn] is an indicator for each of the four quartiles based on the target firm's pre-acquisition worker departures to startups (5 years old or younger). Standard errors, clustered at the firm level, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Linear Regressions on Employee Spawning: Acquired Workers vs. Regular Hires

Dependent Variable *Time Window*	(1) Any Spawn by *t+1*	(2) Any Spawn by *t+2*	(3) Any Spawn by *t+3*	(4) Related Spawn by *t+1*	(5) Related Spawn by *t+2*	(6) Related Spawn by *t+3*
Acquired Worker	0.0012***	0.0025***	0.0037***	0.0008***	0.0015***	0.0023***
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Mean DV of Regular Hires	**0.0017**	**0.0030**	**0.0047**	**0.0004**	**0.0008**	**0.0013**
Matched Workers	YES	YES	YES	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES	YES	YES	YES
Observations	2,354,000	2,354,000	2,354,000	2,354,000	2,354,000	2,354,000
R-squared	0.0044	0.0048	0.0053	0.0056	0.0058	0.0068

Note: This table is a set of worker-level regressions using OLS. All specifications are based on matched workers using Coarsened Exact Matching. Any Spawn *k* is a binary variable equalling 1 if the worker is a founder of a new firm in year *k*. Related Spawn is a binary variable equalling 1 if the spawned company is in the same industry, measured at the level of 2-digit NAICS, as the target firm. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The Impact of Employee Spawning on Acquirer's Firm Performance

Panel A: Employment Growth (over three years)

	(1A) Unrelated Industry	(1B) Unrelated Industry	(2A) Same NAICS-2	(2B) Same NAICS-2	(3A) Same NAICS-4	(3B) Same NAICS-4	(4A) Same NAICS-6	(4B) Same NAICS-6
	DV: Acquirer's Rate of Employment Growth Between Years t and $t+3$							
Number of Spawned Companies	-0.016***	-0.015***	-0.025***	-0.027***	-0.026***	-0.029***	-0.035**	-0.036**
	(0.004)	(0.004)	(0.007)	(0.007)	(0.009)	(0.009)	(0.014)	(0.014)
Ln(Nb. of Entrants in Industry-Year)		0.010		0.023**		0.011		0.005
		(0.011)		(0.011)		(0.007)		(0.006)
Acquisition Year*Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,200
R-squared	0.160	0.160	0.160	0.161	0.158	0.158	0.157	0.157

Panel B: Revenue Growth (over three years)

	(1A) Unrelated Industry	(1B) Unrelated Industry	(2A) Same NAICS-2	(2B) Same NAICS-2	(3A) Same NAICS-4	(3B) Same NAICS-4	(4A) Same NAICS-6	(4B) Same NAICS-6
	DV: Acquirer's Rate of Revenue Growth Between Years t and $t+3$							
Number of Spawned Companies	-0.011*	-0.011*	-0.020**	-0.021**	-0.037***	-0.037***	-0.051**	-0.049**
	(0.006)	(0.006)	(0.009)	(0.009)	(0.014)	(0.014)	(0.023)	(0.023)
Ln(Nb. of Entrants in Industry-Year)		0.003		0.014		0.003		-0.007
		(0.016)		(0.016)		(0.010)		(0.009)
Acquisition Year*Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,700	1,700	1,700	1,700	1,700	1,700	1,700	1,700
R-squared	0.179	0.179	0.180	0.181	0.182	0.182	0.181	0.181

Note: This table shows a series of firm-level OLS regressions on the acquirer's long-run performance. *Number of Entrants* is the total number of new firms born during the acquisition year in the same industry, where same industry is defined at the level of corresponding column (e.g., NAICS-2 for columns 2A and 2B, and NAICS-4 for columns 3A and 3B). All specifications control for acquirer's firm age, included as four separate indicator variables for each quartile. State and Industry (NAICS-2) fixed effects are based on those of the acquiring firm. A new firm is unrelated if its NAICS-2 industry is different from that of the original target firm. To calculate growth, DHS (1996) growth measures are used (See Section 3.4). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1